

# Orientation Prediction with a Cane-wearable Device for Safe Cane Mobility by Persons with Visual Impairment.

Gagandeep Singh, Mohd. Nadir, Rachit Thukral, Piyush Chanana, P. V. M. Rao and Rohan Paul  
Indian Institute of Technology Delhi, India

**Abstract**—Maintaining correct lateral angular coverage of the white cane or electronic canes is crucial for a visually challenged person while moving independently. Incorrect angular side-to-side holding can lead to collisions with obstacles and injuries to a person. This paper introduces a device that uses proprioceptive (IMU) sensing data to predict the instantaneous lateral angle of the cane as the person is tapping side-to-side. Central to the system is a transformer-based architecture that regresses over the lateral angle realized on an embedded architecture. We tackle the challenge of labeling by supervising the model via a classical signal processing approach making the approach scalable and practical. The predictions are used to provide the end user acoustic cues to aid in self-correcting the angle as well as a time-stamped log for the mobility trainer to analyze. This work takes the first step in the direction of intelligent wearable/robotic aids for blind persons that can aid in safe independent mobility

## I. INTRODUCTION

Safe independent mobility is a day-to-day challenge for persons with blindness. They often rely on White Cane to tap side-to-side to detect obstacles on the ground and prevent collisions. While the traditional white canes are still popular a number of Electronic Travel Aids (ETAs) have emerged in the form of electronic canes that use directed sensing for detecting obstacles in the navigation corridor of the moving person to navigate their environments and avoid obstacles. Despite advanced devices such as the Smartcane[1], Ultracane[2], and WeWalk[3], which are capable of detecting obstacles a few meters away, the efficacy of these aids largely depends on the user's ability to correctly use them while walking. Consequently, proper training in the use of these devices is essential. However, the scarcity of experienced mobility trainers in low/middle income countries poses a significant challenge to providing quality training. We seek to bridge the training gap resulting from the scarcity of professional trainers.

In this work, we present the design, implementation, and user evaluation of a device that uses proprioceptive sensing (accelerometers/gyroscope) to predict the instantaneous lateral angle of the cane with respect to the mid-sagittal plane of the person while the person is walking. The device is mounted on the white cane along the handle and does not interfere with the normal tapping and detection functionality of the device during use. The device uses a neural network (transformer-based architecture) to predict the swing angle and assists the visually impaired user to self-correct the swing motion by producing an auditory cue enabling self-learning. Furthermore, the system captures the log of a user's



Fig. 1. Visually Impaired persons rely on the sideways tapping action of a cane to avoid obstacles. (a), (b) User using the cane by tapping it sideways to identify obstacles along the way, (c) Prototype Device: Intelligent embedded system for detecting incorrect swing motion and guiding Person with Visual Impairment to self-correct using audio-vibratory feedback.

mobility and transfers it to a remote server for analysis by an Orientation and Mobility (O&M) trainer.

## II. TECHNICAL APPROACH

**Data Generation.** To construct the training dataset, we captured data from a three-axis accelerometer and gyroscope using an LSM6DSOXTR Inertial Measurement Unit (IMU) sensor. The challenges inherent in labeling raw velocity or acceleration data stem from its high sampling rate (6660Hz), noise introduced through the manipulation of the cane (e.g., holding or tapping), and the costs associated with employing sophisticated motion capture technologies for accurate ground truth acquisition. To circumvent the need for specialized hardware, an analysis of the raw IMU sensor data was conducted while the user used it for obstacle detection. It was observed that the gyroscope data exhibited characteristics of simple harmonic motion along the direction of the motion of ETA. Leveraging this insight, a data labeling methodology was developed. The process involved filtering of signal followed by segmentation of the data into batches with a sequence length of 300 and subsequently determining the phase labels by utilizing a combination of trigonometric functions. We define  $\tilde{y} = Estimate(x_{0:t})$ , where  $x_{0:t}$  is the raw IMU signal of sequence length 300 and the "Estimate" function is the estimated label provided by the data labeling pipeline. The data labeling pipeline enables large-scale data

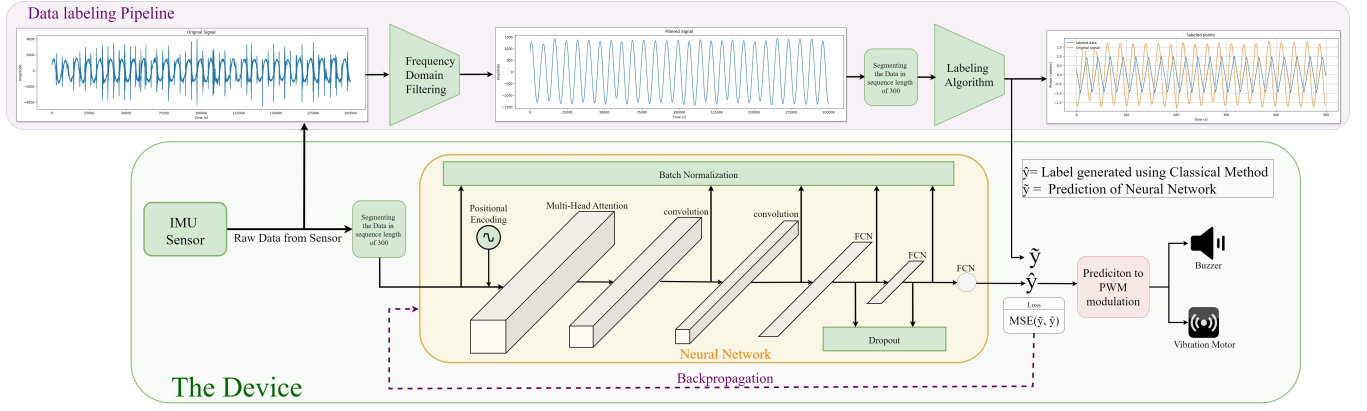


Fig. 2. The ground truth labels were generated using a data labeling pipeline which takes  $x_{0:t}$  as input and provides the pseudo labels  $\tilde{y}$  as output (top). A transformer-based neural network is implemented on an embedded processor which takes  $x_{0:t}$  as input and produces the predictions  $\hat{y}$  as output (bottom).

labeling by providing ground truth after observing raw data for 45 milliseconds, a speed that is too rapid for manual annotation. Although this approach may introduce minor inaccuracies in the labeling, empirical evidence from our study suggests that it yields good performance metrics for our applications. For the assembly of our dataset, we recorded the IMU sensor data over approximately two minutes, capturing lateral cane movements ranging from -20 to +20 degrees, and integrated this with additional data recorded during lateral movements extending from -40 to +40 degrees, over a comparable duration.

**Neural Network.** was developed to estimate the instantaneous phase angle based on velocity and acceleration measurements from an Inertial Measurement Unit (IMU) sensor, which is inherently noisy. The proposed neural network employs a Transformer[4] based architecture, comprising approximately 21,000 parameters. For the backpropagation of loss, We define  $\hat{y} = \text{NeuralNetwork}(x_{0:t})$ , the “*Neural-Network*” function is the prediction of the Neural Network. The loss =  $\mathcal{L}(\tilde{y}, \hat{y})$ , where  $\mathcal{L}$  is Mean Squared Error (MSE) function. This Neural Network was trained and subsequently deployed on a microprocessor with a minimal hardware footprint. To facilitate the deployment of the neural network on such constrained hardware environments, the TensorFlow[5] Lite API was utilized. This API enables the conversion of complex neural network models into a TensorFlow Lite (TFLite) format, significantly more suited for embedded processors due to its reduced size and computational demand.

### III. RESULTS

The performance of the neural model and its real-world applicability were rigorously evaluated in this study. The model’s predictive accuracy was assessed using a test dataset comprising 1,510 samples, where it achieved a mean squared error of 0.0052, indicating high confidence in swing angle recognition. Additionally, real-world tests further validated the neural model’s utility, enabling the differentiation of swing patterns through the visual analysis of graphical plots generated from the observed data. All these computations were done on a Raspberry Pi Zero 2W in approximately 20

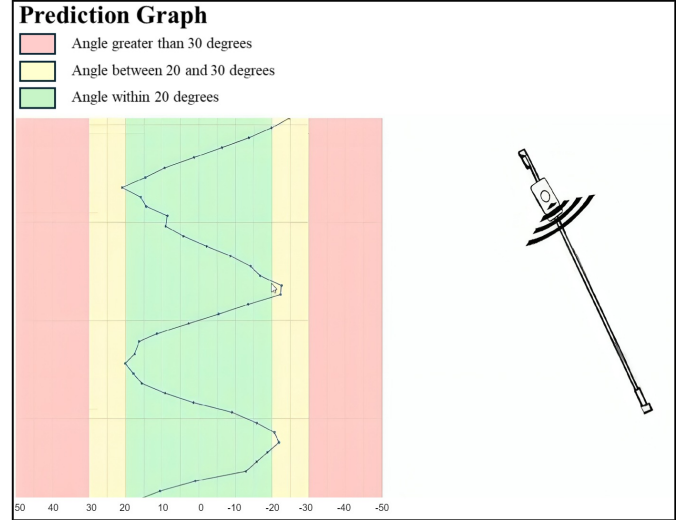


Fig. 3. Vertical graph plot on an external device to assess the instantaneous lateral angle of the cane, red: angle exceeding 40 degrees, green: within 20 degrees, yellow: 20 to 30 degrees (left). A real-time rotational animation of the cane provides an intuitive visual cue of its swing angle (right).

milliseconds. A video link of the demo can be found *here*. Tests on outdoor settings are underway. This work takes a first step in the direction of wearable intelligent devices to aid mobility training for persons with visual impairment.

### IV. CONCLUSIONS

This study has shown promising results for real-time prediction of the cane’s lateral angle. Our results demonstrate the feasibility of using learning-based methods in applications where manually annotated data are difficult to obtain. Our future work will involve integrating feedback mechanisms into the device to help visually impaired individuals correct the lateral angle in real-time. Additionally, we will gather data from O&M trainers and conduct anthropometric studies on multiple users to reduce variation between users.

### REFERENCES

- [1] “Smartcane.” <https://assistech.iitd.ac.in/smartcane.php>.

- [2] “Ultracane.” <https://www.ultracane.com/>.
- [3] “Wewalk.” <https://wewalk.io/en/>.
- [4] C. Subakan, M. Ravanelli, S. Cornell, M. Bronzi, and J. Zhong, “Attention is all you need in speech separation,” in *ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 21–25, 2021.
- [5] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mané, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viégas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng, “TensorFlow: Large-scale machine learning on heterogeneous systems.” <https://www.tensorflow.org/>, 2015. Software available from [tensorflow.org](https://www.tensorflow.org/).